SITE-SPECIFICITY OF CERES-MAIZE MODEL PARAMETERS: A CASE STUDY IN THE SOUTHEASTERN US COASTAL PLAIN

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ABSTRACT

The number of possible combinations of soils, crops, and weather that need to be examined while developing fertilizer and other input recommendations for precision farming suggests that models of crop growth should be quite useful. However, it is not yet known whether the models are suitably accurate, nor are there sufficient site-specific inputs for most situations. This study attempted to determine how spatially precise soil characteristics needed to be if CERES-Maize model results were to be descriptive of spatial observations. Both V3.1 and V3.5 were examined. Detail of inputs ranged from the usual soil survey information for typical pedons, up to field-observed soil, infiltration, and crop characteristics. In this study, model performance overall was disappointing and was not significantly improved by increasing the level of detail.

INTRODUCTION

Crop growth models are such an attractive tool for testing scenarios that they have increasingly attracted attention within the site-specific farming community. Several model/GIS combinations can ease the tedium of managing data files and running models, yet modeling success for site-specific agriculture remains mixed. The most-commonly cited reason for poor performance of models is the lack of site-specific inputs. Collecting such data at spatial sampling densities useful for site-specific modeling is quite labor-, time-, and cost-intensive. Until instruments or models to provide such information become available, modelers must compromise among conflicting objectives that include accuracy, availability of data, and cost of acquiring data not previously available. The question remains, how site-specific must the inputs be for the model to provide useful results?

Using models for scenario testing and prediction in site-specific agriculture requires two important conditions. These are suitable accuracy, which has been discussed elsewhere (Sadler and Russell, 1997), and large quantities of site-specific soil, crop, and weather information. Unavailability of the latter is why most studies reporting success using models for simulating spatial variability in yield or other crop responses have used some kind of parameter fitting (Batchelor and Paz, 1998; Barnes *et al.*, 1998; Braga and Jones, 1998; Sudduth *et al.*, 1998). There appears to be no other way to achieve explanatory model results with currently available data. However, fitting the model parameters based on minimizing variance from observed results also requires two conditions. First is that the model behave appropriately. Second is that no important inputs are left out of the process. For optimum performance of the fitting procedure, all important inputs, save the one(s) being fitted, must be supplied with appropriate site-specific values.

This raises the question of which inputs are important. One would hope that research could identify these parameters on small-plot or limited-scope experiments. The process becomes a parallel sensitivity analysis involving both model runs and field observations. Ongoing modeling studies in the US Coastal Plains Center Site-Specific Farming Project provided an opportunity to study the performance of the CERES-Maize model (Tsuji, *et al.*, 1994) under a series of model inputs that were incrementally more site-specific regarding soil characteristics. The model sequence was compared with data collected during the 1993 corn season, which suffered a severe drought (Sadler *et al.*, 1995a).

METHODS

A series of six model runs was designed, starting with the conventional soils data available from the usual soil surveys (designated Level 1), progressing down the spatial scale to quite intensive field measurements (Level 6). These runs were conducted with CERES-Maize, which is a daily-time-step model of corn growth and yield. Runs were made with both V3.1 (Tsuji, *et al.*, 1994) and its update, V3.5 (Hoogenboom *et al.*, 1998). To evaluate the changes between versions, a preliminary comparison of yield results for a 7-year corn yield dataset (1985, 1986, 1988, 1992, 1993, 1995, 1997) from Florence, SC, USA, was made as well as performing the detailed analyses of the 1993 dataset.

Measurements were taken during the 1993 crop season, preliminary results for which are given in Sadler *et al.* (1995a). Soil water contents were available from time-domain reflectometry (TDR) measurements at eight sites with four soil types. Measurements of phenology, LAI, biomass, yield components, and yield, were also available at those sites.

Level 1. The normal starting point for modeling studies contrasting soil types is the data available from typical soil descriptions, supplemented where possible with State Experiment Station bulletins. For this reason, our Level 1 estimates of soil parameters were extracted from typical descriptions for four soil map units (Goldsboro-GoA, Norfolk-NkA, Bonneau-BnA, and Coxville-Cx). The descriptions were taken from the 1:1200 soil survey (USDA-SCS, 1986) and from bulletins describing Coastal Plain soils in South Carolina (Peele, *et al.*, 1970) and Georgia (Long, *et al.*, 1969). The physical characteristics for each of the four soil map units are listed in Table 1.

Level 2. The most-apparent and most-easily observed deviation from the typical pedon description is the thickness of the horizons. Therefore, Level 2 involved adjusting layer thickness to match specific profiles, retaining typical descriptions of the layers. The depths of the profiles were measured at each of eight sites where collateral data were collected during the 1993 corn season. The changes from Level 1 to Level 2 are listed in Table 2.

Level 3. Variations in soil physical properties, including texture and the associated hydraulic characteristics, have been suspected as causing significant variation in water relations. Level 3 added the adjustment of lower and upper limits of water holding capacity to estimates obtained both from field TDR measurements and from laboratory water retention curves obtained on selected soils. The values used are listed in Table 3.

TABLE 1. Characteristics for the 4 typical soils. Abbreviations are depth to bottom of layer(SLB), lower limit of available water (SLLL), drained upper limit (SDUL), saturation water content (SSAT), and bulk density(SBDM).

GoA	SLB	SLLL	SDUL	SSAT	SBDM	NkA	SLB	SLLL	SDUL	SSAT	SBDM
Layer	cm	-	-	-	g/cm^3	Layer	cm	-	-	-	g/cm^3
1	9	0.062	0.162	0.270	1.54	1	9	0.054	0.123	0.260	1.52
2	18	0.058	0.168	0.273	1.54	2	17	0.052	0.127	0.261	1.52
3	28	0.059	0.181	0.270	1.81	3	30	0.061	0.162	0.260	1.71
4	38	0.058	0.182	0.270	1.81	4	51	0.162	0.271	0.353	1.42
5	64	0.179	0.293	0.354	1.67	5	81	0.175	0.283	0.332	1.42
6	81	0.232	0.346	0.366	1.52	6	122	0.173	0.283	0.332	1.42
7	102	0.241	0.352	0.362	1.52	7	132	0.171	0.283	0.332	1.42
8	127	0.241	0.352	0.362	1.52	8	165	0.171	0.283	0.332	1.42
9	173	0.241	0.352	0.362	1.52	9	199	0.171	0.283	0.332	1.42
10	200	0.241	0.352	0.362	1.52						

BnA	SLB	SLLL	SDUL	SSAT	SBDM	Cx	SLB	SLLL	SDUL	SSAT	SBDM
Layer	cm	-	-	-	g/cm^3	Layer	cm	-	-	-	g/cm^3
1	12	0.045	0.121	0.277	1.50	1	10	0.137	0.254	0.336	1.57
2	25	0.043	0.125	0.279	1.50	2	20	0.132	0.254	0.337	1.57
3	40	0.047	0.142	0.250	1.69	3	33	0.130	0.254	0.337	1.67
4	61	0.046	0.143	0.251	1.69	4	64	0.220	0.341	0.386	1.60
5	76	0.133	0.244	0.311	1.65	5	76	0.220	0.341	0.386	1.53
6	97	0.150	0.260	0.319	1.60	6	108	0.220	0.341	0.386	1.53
7	117	0.150	0.260	0.319	1.60	7	132	0.221	0.342	0.386	1.53
8	144	0.183	0.293	0.344	1.60	8	162	0.240	0.356	0.395	1.53
9	172	0.183	0.293	0.344	1.60	9	192	0.240	0.356	0.395	1.53
10	200	0.183	0.293	0.344	1.60	10	222	0.240	0.356	0.395	1.53

TABLE 2. Changes in horizon thickness from Level 1 to Level 2. Depth is to bottom of the layer.

Layer	Depth cm	Depth cm	Depth cm	Layer	Depth cm	Depth cm	Depth cm
	Typical	Site 1	Site 2		Typical	Site 3	Site 4
GoA	Level 1	Level 2	Level 2	NkA	Level 1	Level 2	Level 2
1	9	15	11	1	9	14	13
2	18	30	23	2	17	28	25
3	28	50	41	3	30	34	50
4	38	75	60	4	51	56	75
5	64	100	100	5	81	78	100
6	81	127	127	6	122	100	122
7	102	173	173	7	132	122	132
8	127	200	200	8	165	132	165
9	173			9	199	165	199
10	200			10		199	
	Typical	Site 5	Site 6		Typical	Site 7	Site 8
BnA	Level 1	Level 2	Level 2	Cx	Level 1	Level 2	Level 2
1	12	15	16	1	10	16	10
2	25	30	32	2	20	32	25
3	40	48	48	3	33	48	40
4	61	66	64	4	64	64	59
5	76	83	82	5	76	82	78
6	97	100	100	6	108	100	100
7	117	117	117	7	132	132	132
8	144	144	144	8	162	162	162
9	172	172	172	9	192	192	192
10	200	200	200	10	222	222	222

TABLE 3. Soil physical characteristics changed from Level 2 to Level 3. Definitions as in Table 1.

	SLLL	SDUL	SSAT	SLLL	SDUL	SSAT	SLLL	SDUL	SSAT
GoA	Level 2			Level 3 Site 1			Level 3 Site 2		
1	0.062	0.162	0.270	0.060	0.165	0.270	0.030	0.145	0.270
2	0.058	0.168	0.273	0.050	0.140	0.273	0.055	0.123	0.273
3	0.059	0.181	0.270	0.050	0.170	0.270	0.055	0.155	0.270
4	0.058	0.182	0.270	0.170	0.300	0.310	0.050	0.150	0.270
5	0.179	0.293	0.354	0.200	0.350	0.354	0.270	0.370	0.380
6	0.232	0.346	0.366	0.232	0.346	0.366	0.232	0.346	0.366
7	0.241	0.352	0.362	0.241	0.352	0.362	0.241	0.352	0.362
8	0.241	0.352	0.362	0.241	0.352	0.362	0.241	0.352	0.362
NkA	Level 2			Level 3 Site 3			Level 3 Site 4		
1	0.054	0.123	0.260	0.053	0.180	0.260	0.030	0.175	0.260
2	0.052	0.127	0.261	0.035	0.133	0.261	0.073	0.185	0.261
3	0.061	0.162	0.260	0.068	0.185	0.260	0.195	0.295	0.305
4	0.162	0.271	0.353	0.195	0.295	0.353	0.230	0.350	0.355
5	0.175	0.283	0.332	0.168	0.280	0.332	0.240	0.350	0.355
6	0.173	0.283	0.332	0.233	0.348	0.350	0.173	0.283	0.332
7	0.171	0.283	0.332	0.171	0.283	0.332	0.171	0.283	0.332
8	0.171	0.283	0.332	0.171	0.283	0.332	0.171	0.283	0.332
9	0.171	0.283	0.332	0.171	0.283	0.332	0.171	0.283	0.332
10	0.171	0.283	0.332	0.171	0.283	0.332			
BnA	Level 2			Level 3 Site 5			Level 3 Site 6		
1	0.045	0.121	0.277	0.048	0.145	0.277	0.021	0.159	0.277
2	0.043	0.125	0.279	0.055	0.135	0.279	0.015	0.120	0.279
3	0.047	0.142	0.250	0.045	0.125	0.250	0.029	0.200	0.250
4	0.046	0.143	0.251	0.070	0.160	0.251	0.070	0.213	0.251
5	0.133	0.244	0.311	0.180	0.270	0.311	0.150	0.287	0.311
6	0.150	0.260	0.319	0.225	0.350	0.360	0.180	0.290	0.319
7	0.150	0.260	0.319	0.150	0.260	0.319	0.150	0.260	0.319
8	0.183	0.293	0.344	0.183	0.293	0.344	0.183	0.293	0.344
9	0.183	0.293	0.344	0.183	0.293	0.344	0.183	0.293	0.344
10	0.183	0.293	0.344	0.183	0.293	0.344	0.183	0.293	0.344
Cx	Level 2			Level 3 Site 7			Level 3 Site 8		
1	0.137	0.254	0.336	0.035	0.215	0.336	0.065	0.205	0.336
2	0.132	0.254	0.337	0.025	0.203	0.337	0.075	0.205	0.337
3	0.130	0.254	0.337	0.048	0.226	0.337	0.018	0.196	0.337
4	0.220	0.341	0.386	0.040	0.230	0.386	0.050	0.190	0.386
5	0.220	0.341	0.386	0.155	0.295	0.386	0.090	0.240	0.386
6	0.220	0.341	0.386	0.200	0.240	0.386	0.240	0.400	0.410
7	0.221	0.342	0.386	0.221	0.342	0.386	0.221	0.342	0.386
8	0.240	0.356	0.395	0.240	0.356	0.395	0.240	0.356	0.395
9	0.240	0.356	0.395	0.240	0.356	0.395	0.240	0.356	0.395
10	0.240	0.356	0.395	0.240	0.356	0.395	0.240	0.356	0.395

Level 4. Field observations of runoff when modeled runoff was zero suggested that the modeled infiltration needed improvement. Stone and Sadler (1991) examined curve number and Green-Ampt (Green and Ampt, 1911) infiltration models, observing that approximately half the variance between observed and modeled yield could be explained by differences in infiltration. Thus, Level 4 included field observations of infiltration, as calculated from the TDR measurements (Haan *et al.*, 1994; Schwab *et al.*, 1993).

Levels 5 and 6. For rainfed agriculture, variable-rate adjustment of seeding rate has been proposed as a way to manage limited within-season water supplies. Consequently, sensitivity to plant population and producing plant population was examined. Level 5 included field observations of plant population at each site, and Level 6 limited the population to plants producing ears.

RESULTS AND DISCUSSION

Prior experience with CERES-Maize resulted in simulations of corn yield that were higher than observed yields for low-yielding years both in our experience (Sadler *et al.*, 1998) and other's (Batchelor *et al.*, 1998). The runs in Sadler *et al.* (1998) were conducted using crop parameters, particularly maximum kernel number, developed locally. However, the V3.5 genotype file contained an entry for the cultivar used (Pioneer 3165) that, when run with V3.1, significantly improved the estimate of the long-term mean. Therefore, all runs for both versions used the new crop parameters.

The immediately obvious result from the comparison between versions was that for the combinations of soil, crop, and weather files used, Version 3.5 simulated corn yields approximately 1.5 Mg/ha lower than did Version 3.1 (see Figure 1). Version 3.5 approximated observed yields only in the lowest-yielding years. At the present, we are unable to explain the reasons for this result.

Yield results from Level 1 runs (Figure 2) met expectations developed in several similar simulation experiments using soil characteristics from typical pedon descriptions (Sadler *et al.*, 1995b; Sadler *et al.*, 1998). However, results from the entire series of increasingly site-specific parameters were disappointing (Figures 2 and 3 for Levels 1-4). Results from Levels 5 and 6, not shown, were indistinguishable from those of Level 4, reflecting insensitivity to plant population in the ranges observed.

The sequence of simulated yield shows that very little of the measured variance is captured by the simulation, at any level of specificity of parameters. In general, the V3.5 model estimates the field mean reasonably well for Levels 1-3, and underestimates the mean for Level 4, when known errors in infiltration are corrected. A review of the results for seed weight illustrates the reason for the drop in yield for Level 4, where seed weight for V3.5 was 50% less than for V3.1. Interestingly, although V3.1 simulated higher grain numbers than V3.5 for Levels 1-3, the relative position reversed for Level 4. In general, V3.5 performed better than V3.1 in estimating grain number for all input levels. It also performed equal to or better than V3.1 for maximum LAI.

Increasing site-specificity of parameters did not increase the predictive capability of the model for the explanation of within-field, or soil-to-soil, variability, despite some improvement in the estimate of the mean. In general, the variance in simulated results was much less than the variance in observed results. This holds for multiple-year simulations on the complete data set as well (Figure 1). Several reasons for this observation can be proposed, and there is value to this speculation for modeling for precision agriculture.

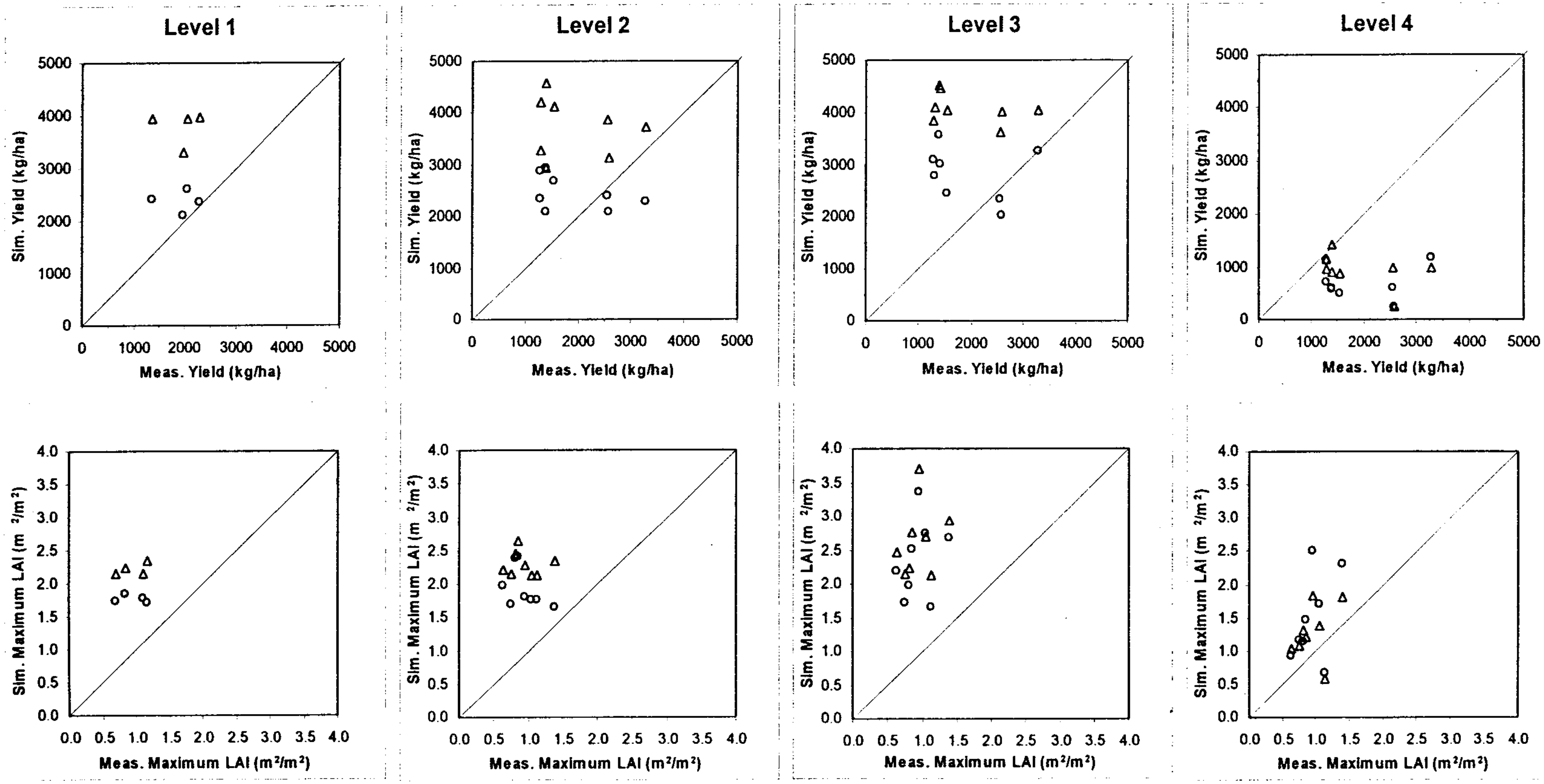

FIGURE 2. (Top row) Corn yield as simulated by CERES-Maize V3.1 (triangles) and V3.5 (circles) as a function of the mean measured yield for all plots within 10 m of the site during 1993, for the Levels 1 through 4 soil parameters. (Bottom row) Maximum LAI as simulated by CERES-Maize V3.1 (triangles) and V3.5 (circles) as a function of the mean measured LAI at mid-silk for the site during 1993, for the Levels 1 through 4 soil parameters.

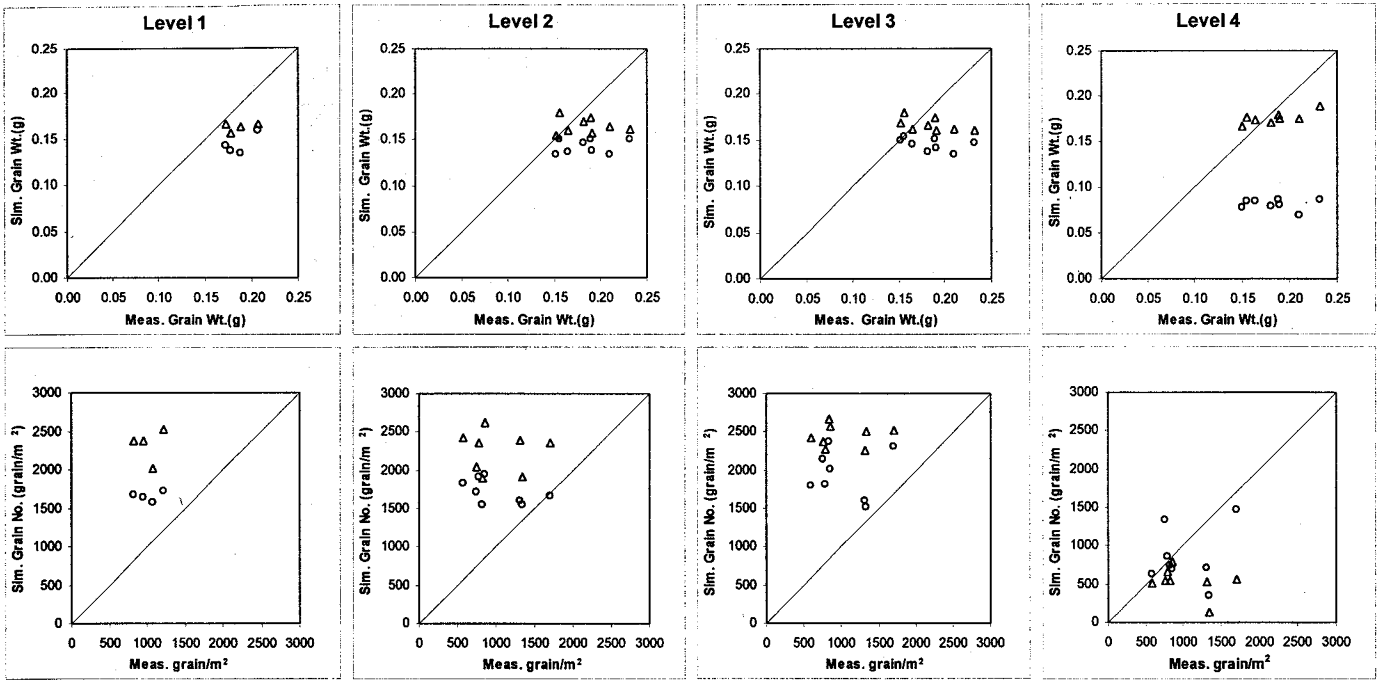

FIGURE 3. (Top row) Kernel weight as simulated by CERES-Maize V3.1 (triangles) and V3.5 (circles) as a function of the mean measured kernel weight for the site during 1993, for the Levels 1 through 4 soil parameters. (Bottom row) Kernel number as simulated by CERES-Maize V3.1 (triangles) and V3.5 (circles) as a function of the mean measured kernel number for the site during 1993, for the Levels 1 through 4 soil parameters.

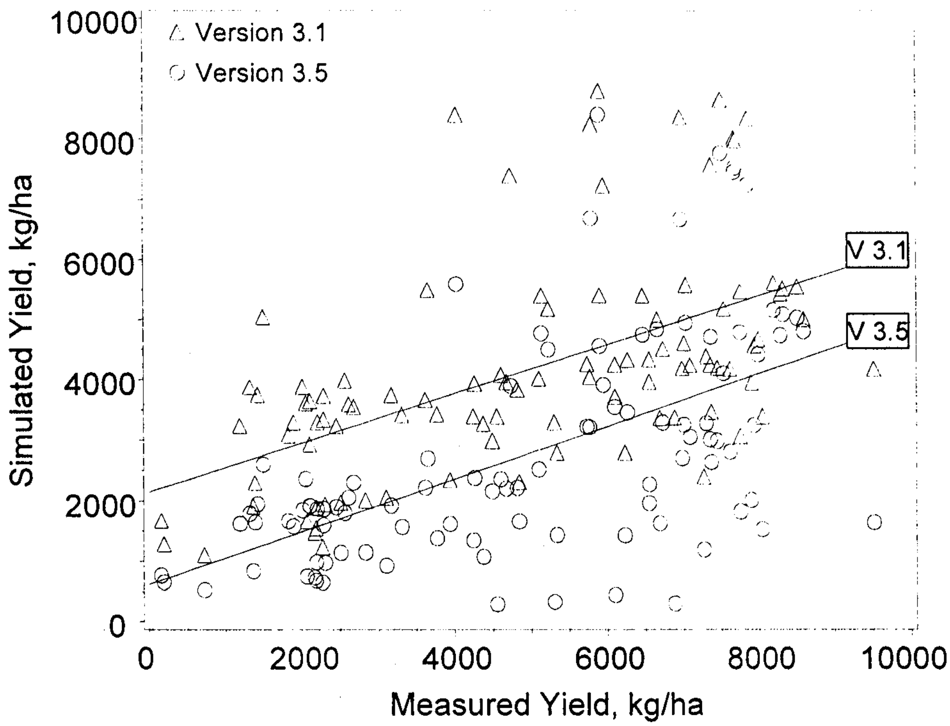

FIGURE 1. Corn yield as simulated by CERES-Maize V3.1 (triangles) and V3.5 (circles) as a function of the mean measured yield for the soil map unit, for all soils and all years (1985, 1986, 1988, 1992, 1993, 1995, 1997) at Florence, SC. Lines indicate linear regression through values for each model version (r^2<0.04).

First, modelers can make a case that the soil parameters are not yet sufficiently representative. This could be either that the parameters were not correct, or that the wrong parameters were chosen. Either way, variation in the soils would not have been captured in the parameters. Theoretically, if the parameters are not representative, the model could be perfect yet still produce the results shown. However, the bulk of all modeling with daily-time-step models has been conducted with specificity approximating that shown in our Level 1. The work involved in producing Level 3 information, let alone Level 4, is cost-prohibitive for even modest use in precision farming. Further, the model has been demonstrated to be relatively insensitive to the parameters assumed constant in the current exercise. So, if input parameters are yet more difficult to obtain, such models would be of limited utility for precision farming.

Second, empiricists could argue that the models are not sufficiently accurate to estimate within-field variance. This could also be true. In general, results obtained by the authors and others have indicated that the CERES-Maize model is a better estimator of the field mean than of within-field variance. Most models were designed to simulate much larger differences in cultivars, soils, and weather than commonly exists within a field. As discussed by Sadler and Russell (1997), models are particularly taxed by requirements of precision farming. Many parameters assumed constant in the development of the model (*e. g.*, canopy temperature) have been shown to be extremely variable within a field (Sadler *et al.*, 1995b). Other difficulties accrue for 1-D models in cases with 3-D variation.

However, a voice of moderation would observe that the real answer likely lies somewhere in between, noting that only in the last few years have studies used models for precision agriculture. For example, the CERES-Maize model lacks structures to account for within-field variation in air and canopy temperature, as well as for certain soil characteristics, any or all of which may be important in this new research area. Further, within-field variation in several parameters was not examined. For our purposes, we will continue to expand our list of candidate parameters to improve model applicability, including use of objective parameterization to place bounds on the soil characteristics not measured. Finally, we encourage researchers to continue to work with the developers of CERES-Maize and other models to improve the utility of these tools for the purposes of precision agriculture.

CONCLUSIONS

Increasing the level of detail regarding the site-specificity of the soil characteristics did not materially improve the fit between the measured and simulated values. From the information available, it cannot be determined whether the cause for the performance stemmed from unrepresentative input parameters or limited model structure.

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